Improvement of Radiative Fluxes for the CERES FluxByCldTyp Data Product Based on Machine Learning Technique

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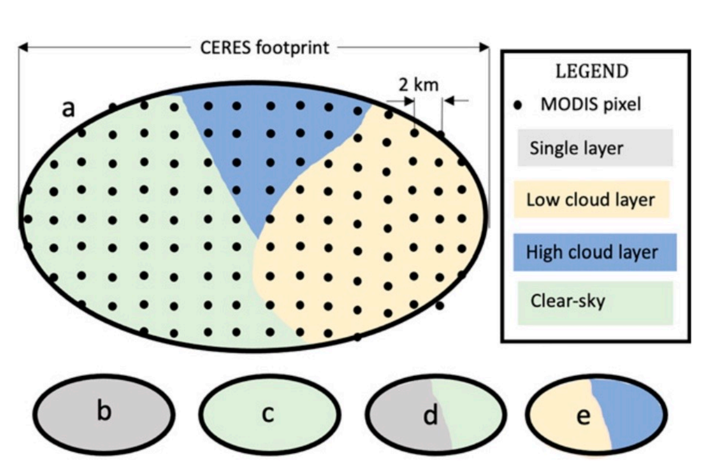
1. Introduction

The NASA Clouds and the Earth's Radiant Energy System (**CERES**) product provides over 20 years of accurately observed top-of-the-atmosphere (TOA) and surface flux data record for climate monitoring and diagnostic studies. To further advance our understanding of the cloud-radiation interaction, a new CERES FluxByCldTyp (FBCT) product has been developed (Sun *et al.* 2022, data portal https://ceres. larc.nasa.gov/data/#fluxbycldtyp-level-3) . It contains radiative fluxes and cloud properties by cloud-type, which is stratified by cloud optical depth and cloud effective pressure. The SW and LW fluxes are derived from MODIS imager narrow-band (NB) radiances. They are converted to broad-band (BB) radiances based on NB2BB empirical linear regression coefficients. The BB radiances are converted to fluxes by angular directional models (ADMs). The whole algorithm is shown in Figure 1. In order to further improve accuracy, this paper uses machine learning technique --- specifically deep neural network (DNN) to convert MODIS NB radiances to BB fluxes.

2. Data and Methodology

a. Data:

The CERES Single Scanner Footprint (SSF) Edition 4A dataset is the main input to the FBCT product. The SSF product contains the observed CERES instrument 20-km nominal footprint TOA radiances, fluxes, and MODIS cloud proper- ties. The CERES footprint is divided into subregions based upon the individual MODIS pixel-level cloud retrievals as shown in Fig. 1 The data used in this study is SSF Ed4 data from Aqua Satellite. Data are sampled every third day in January 2019. The sample size ranges from 6-7 millions for clear sky to 12 millions for cloud sky.



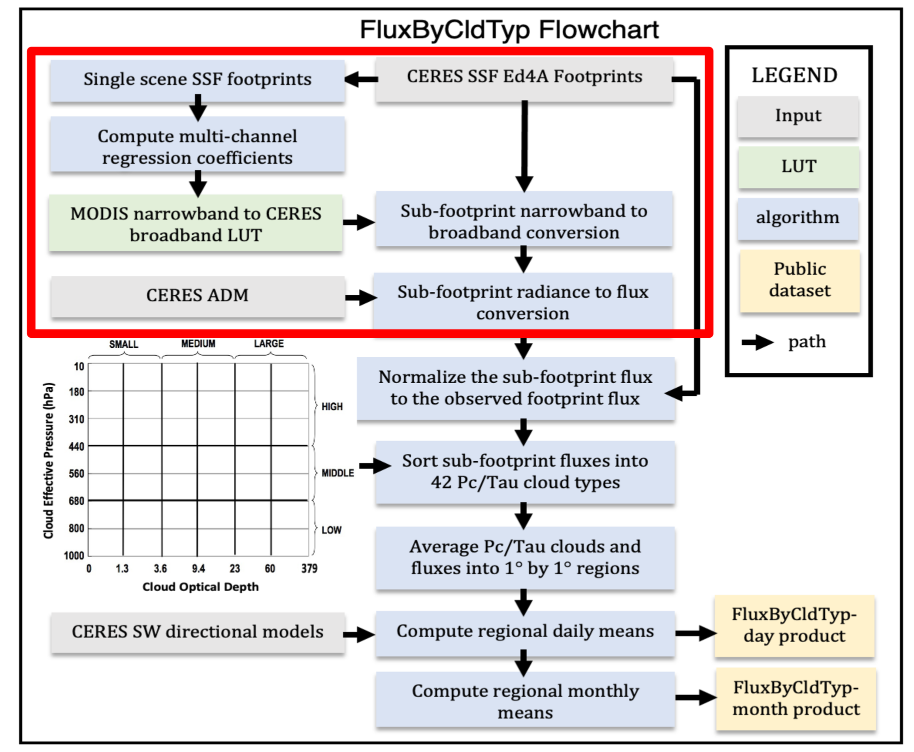
(Sun *et al.* 2022)

Fig. 1. Schematic of the CERES footprint (20km nominal resolution).

b. Methodology:

1) Fig.2 presents the FBCT product flowchart and provides an overview of the inputs and algorithms needed for FBCT processing. This paper will focus on the procedures within the red frame. The rest stay the same.
2) Deep neural network will be used to convert MODIS NB radiances to fluxes either directly (bypassing ADM) or indirectly (still needs ADM). DNN parameters are obtained by machine learning models based on Single scene SSF footprints (case b and c in Fig. 1) input. These DNN parameters will be applied to SSFs with mixed scenes (case d and e in Fig. 1)
3) **DNN model** is illustrated in Fig.3. Besides the input and output layers, it has 5 hidden layers with different nodes from 100 in the first layer to 10 in the 5th hidden layer. The model's hyper-parameters: epoch number is 300, minibatch size is 128, initial learning rate is 0.01 and decreasing with drop rate 0.5, epoch drop rate is 50. The data is split into three groups: 80% training data, 18% development data and 2% test data. Table 1 shows the input parameters for the DNN Model. Both SW and LW use the same clear sky and cloudy sky models.

Clear sky has total of 13 parameters including skin temperature plus other 12 parameters that are also used by cloudy sky model. Surface are classified into 7 types: ocean, forest, savannah, grass, dark desert, bright desert, snow/ice. Including other variables like cloud optical depth does not improve performance.



(Sun *et al.* 2022)

Fig. 2. The CERES FBCT flowchart. The FBCT cloud effective pressure by optical depth cloud-types are shown in the center left and are defined in the same manner as the ISCCP D1 product.

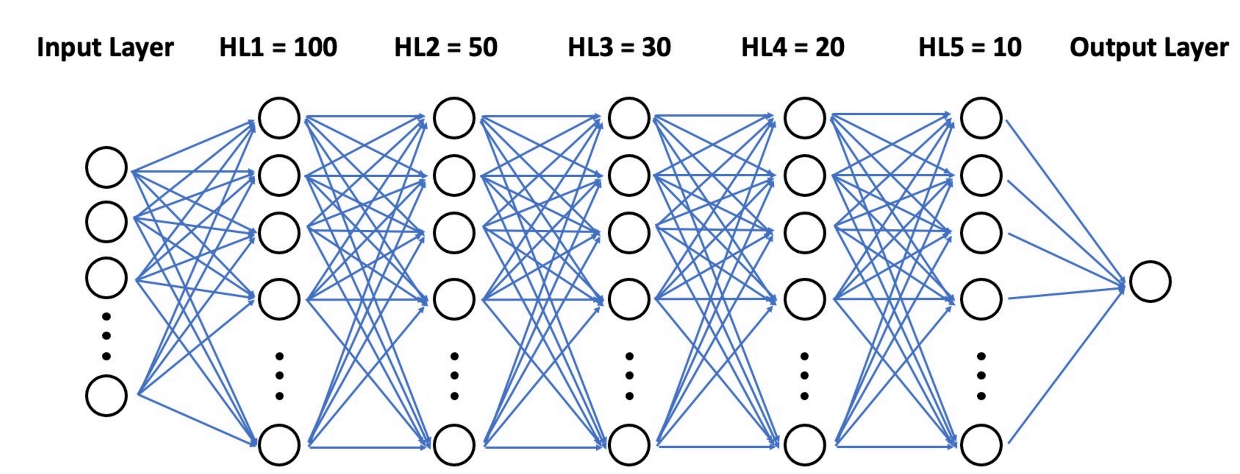


Fig. 3. DNN network diagram with 5 hidden layers and number of nodes for each hidden layer.

	Input Parameters		Total
Clear Sky	5 NB radiances: 0.47μm, 0.65μm, 0.86μm,11μm, 12μm, solar zenith angle (SZA), viewing zenith angle (VZA), relative azimuth angle (RAA), surface type, total precipitable water (TPW), latitude, longitude	Skin Temperature	13
Cloudy Sky			12

Table 1. Input parameters for DNN clear sky and cloudy sky models.

3. Results

As mentioned in section 2b.2, two methods are developed. The first one uses DNN to convert MODIS NB radiances to BB radiance and then convert it to BB flux using ADM (**DNNRad**). The second one converts MODIS BB radiances to BB flux directly without ADM (**DNNFlux**). The trained DNN parameters are applied to SSFs with mixed scenes (Fig. 1) to generate BB flux for each scene (sub-footprint). The fluxes from each sub-footprint are summed to form the total footprint flux. It will be compared against the CERES observed footprint level fluxes provided in the SSF Ed4 dataset.

Fig. 4 shows the SW derived and observed footprint SW flux differences (%) plotted as a function of cloud fraction, cloud effective pressure, cloud effective temperature, cloud optical depth, TPW, SZA, VZA, and surface type. The biases and standard deviations and their variations along the underlying parameters show how well each algorithm does. The smaller values mean improved results. Both DNNRad and DNNFlux show overall improvement over Ed4.1. The most significant improvement is against the cloud optical depth for both DNNs. The two DNN methods give similar results. This indicates future FBCT edition can bypass ADM which significantly reduces the code complexity. Fig. 5 shows the LW results.

Both DNNRad and DNNFlux show overall improvement over Ed4.1. Like SW, with or withour ADM give about the same results.

a) DNNRad SW b) DNNFlux SW c) Ed4.1 SW

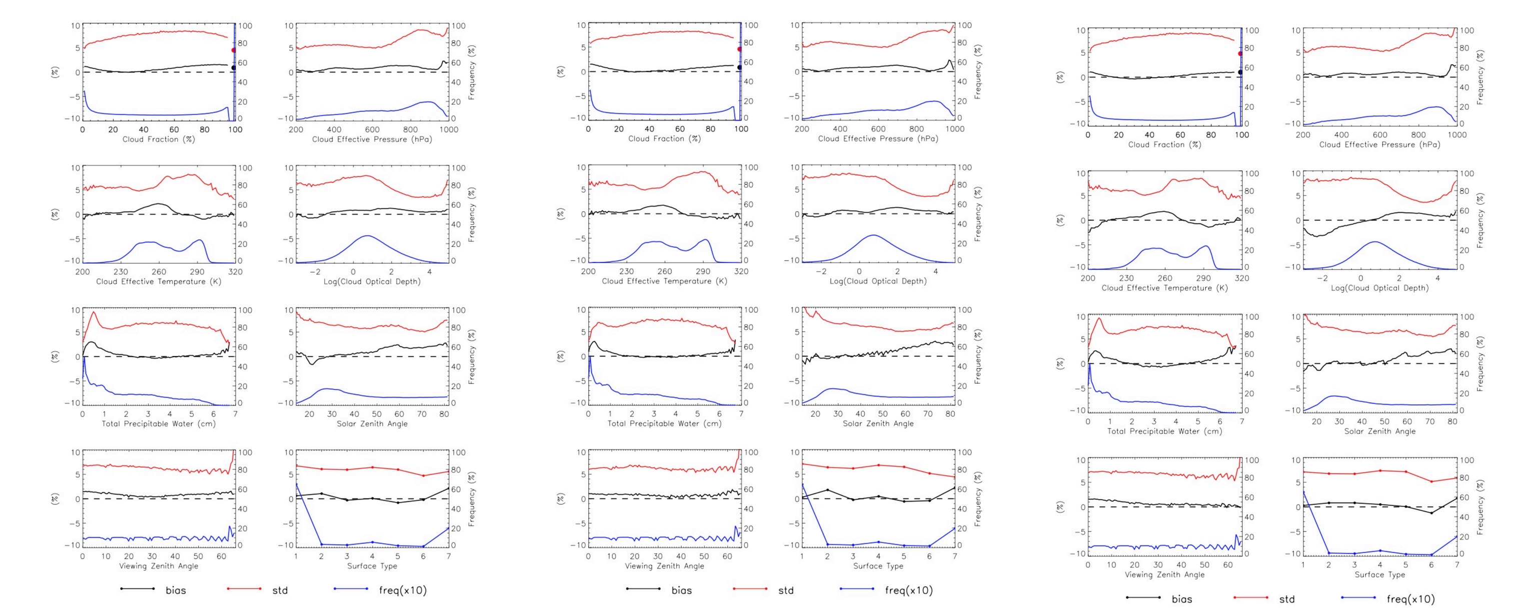


Fig. 4 January 2019 Aqua derived SW SSF fluxes vs CERES observed SSF fluxes. Bias (%, black), standard deviation (%, red) and frequency (%x10, blue)

a) DNNRad LW b) DNNFlux LW c) Ed4.1 LW

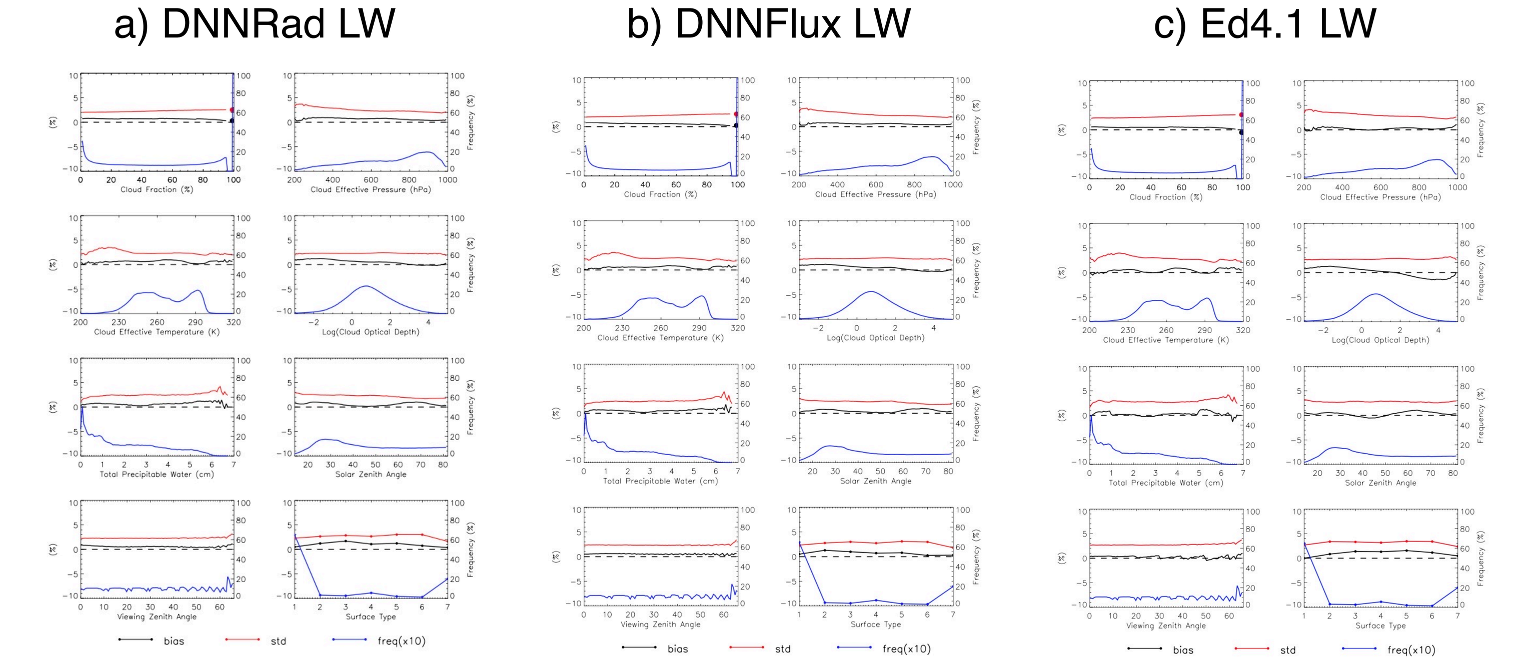


Fig. 5 same as Fig. 4 but for LW.

a) DNNRad SW b) DNNFlux SW c) Ed4.1 SW

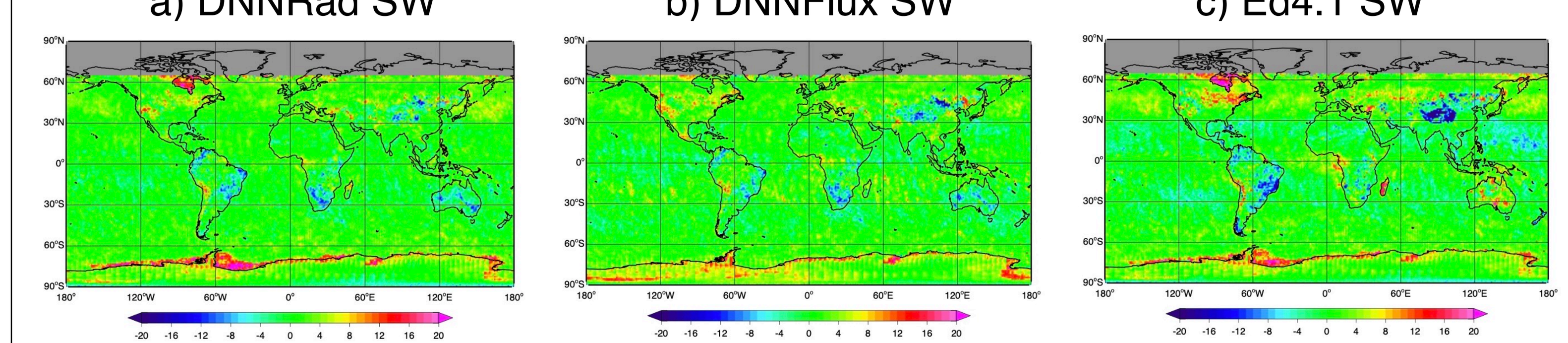


Fig. 6 Derived SW fluxes minus observed fluxes based on mixed scene footprints (unit W/m²).

a) DNNRad LW b) DNNFlux LW c) Ed4.1 LW

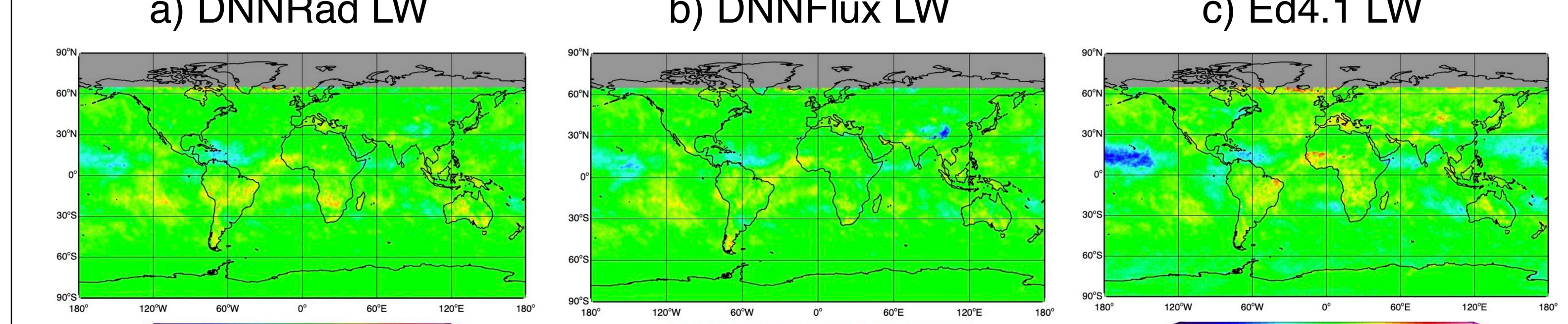


Fig. 7 same as Fig. 6 but for LW.

Fig. 6 and Fig. 7 show the biases of SW and LW fluxes between derived fluxes and CERES observed fluxes. Both DNNRad and DNNFlux show improvement for SW and LW over Ed4.1. DNNFlux SW significantly reduces biases over Hudson bay and Weddell Sea regions. DNN LW shows very small differences between the two new methods. Again, ADM is not required to obtain accurate FBCT fluxes.

4. Summary and future work

Two methods based on DNN are developed to improve fluxes in FBCT product. They both show improvement over Ed4.1. The two methods give about the same results and ADM is not required in future FBCT code. Further improvement may come from using different MODIS NB channels.